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Multi-disruption criticality analysis in bioenergy-based eco-industrial parks via the P-graph approach

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ABSTRACT

Bioenergy-based eco-industrial parks or "bioenergy parks" are integrated networks of biomass processing industries that optimally allocate products, by-products, waste, as well as common utilities in order to further improve sustainability. This multifunctional system produces high value products such as power, biochar, biochemicals, etc. alongside with the conventional biofuels (e.g., bioethanol). However, these networks are characterized as inherently vulnerable to cascading disruptions in cases of inoperability (i.e., reduction in production levels) of one or more of its component bioenergy plants. The inoperability of bioenergy plants can be caused by supply-side disruptions due to reductions in the available biomass feedstocks (i.e., caused by climate change-induced events) as well as due to seasonal variations in the demand for bioenergy products. It is therefore essential to incorporate these factors in the systematic risk analysis prior to designing of bioenergy parks. This work thus develops an extension to the P-graph based method for criticality analysis in bioenergy parks considering multiple supply-side and demand-side perturbation scenarios. Results show that the average net output reduction in the bioenergy park is higher for multiple plant disruption scenarios and criticality of bioenergy plants is greatly influenced by variations in product demands. The proposed method can be used in the long-term planning and developing of robust bioenergy parks while considering both uncertainties in the supply and demand. A bioenergy park case study is presented to demonstrate the applicability of the P-graph based approach.

1. Introduction

The use of bioenergy is seen as a potential strategy to mitigate climate risks via the reduction in the atmospheric greenhouse gas (GHG) emissions and to attain energy security (IEA, 2016). Thus, the demand for bioenergy is continually increasing as production facilities pursue sustainability by looking for reliable alternatives to fossil fuels (Hong et al., 2016). A recent review paper by Sadhukhan et al. (2018) presents the importance of utilizing bioenergy in achieving sustainable development. Bioenergy parks or bioenergy-based eco-industrial parks (EIPs) are interconnected biomass-based production plants that achieve sustainable operations through material and energy exchanges. It is a specific type of an industrial symbiosis (IS) network that optimally allocates products, by-products, waste, and utilities of plants which are collocated within a particular geographical area (Chertow, 2000). Well-known examples of IS networks include the Kalundborg complex in Denmark (Jacobsen, 2006) and the Handelö bioenergy complex in Sweden (Martin and Eklund, 2011). The bioenergy park concept is originally proposed by Martin and Eklund (2011) to increase the performance of biofuel production facilities and to address related sustainability issues (e.g., energy efficiency, by-products reuse). This industrial complex-type integrated bioenergy system (IBS) has the potential to reduce carbon emissions (Ubando et al., 2014) and increase the profitability of each participating plant (Ng et al., 2014). In addition, the concept of a biorefinery-based IS network is presented in the work of Santos and Magrini (2018) as a strategy for regional development. However, such integrated systems and eco-industrial parks in general are known to be inherently vulnerable to cascading failures caused by the inoperability of one or more of its components (Zhu and Ruth, 2013). This inoperability or capacity disruption results in a deviation from the baseline state (i.e., desired net output) of the bioenergy park. The concept of inoperability is adapted from the work of Haimes and Jiang (2001) and defined as the decrease in the production level or capacity of an infrastructure or unit.

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Climate change-induced events such as drought, extreme weather patterns, and pest infestation to crops can cause supply-side disruption (Langholtz et al., 2014; Goebel and Sallam, 2017). Bioenergy production is dependent on the availability of biomass feedstocks, thus, any reduction in supply will greatly affect the entire supply chain including biomass-based facilities. Tan et al. (2017b) emphasized the vulnerability of industrial networks and stated the need to develop "climate-proof" systems by focusing on its robustness and resilience. To add, Benjamin et al. (2015c) concluded that multiple-plant supply-side disruption scenarios greatly affect the robustness (i.e., disruption consequence) and resilience (i.e., measured in recovery time) of the bioenergy park. Aside from this, a robust bioenergy park must be able to handle potential uncertainties in the product demands as well (Yue et al., 2014). Demand uncertainty is defined by Awudu and Zhang (2012) as the unpredictability of the variation in the amount and timing of demand in the biofuel supply chain. This parameter is also considered in this study since it will greatly affect the sustainability of the bioenergy park in terms of economic profitability. The likelihood of developing under-capacity or over-capacity systems are significantly reduced as well when demand uncertainties are incorporated in the model (Tay et al., 2013). Hong et al. (2016) also noted that in order to develop robust and flexible supply chains, the system must anticipate possible fluctuations in the demand for bioenergy. Aside from this, temporal variations of supply and demand within an IS network should be addressed as well (Herczeg et al., 2018). A risk analysis framework, considering all these factors, is therefore necessary prior implementing the bioenergy park strategy.

Criticality analysis is a risk-based method developed by Benjamin et al. (2015a) to determine the effect of capacity disruptions in various integrated energy systems (IES) such as a polygeneration network. A recent work by Andiappan et al. (2017) utilized this approach to identify the most crucial process unit in a biomass energy system (BES) prior implementing equipment redundancy based on financial and reliability restrictions. Criticality analysis quantifies the reduction in the net output of a particular product stream brought about by the decrease in the production level or inoperability of a component plant (or process unit). The plants in a given network are then ranked based on criticality (i.e., change in net output) to determine the most crucial component that will require risk mitigation strategies (e.g., increasing capacity redundancy). This risk-based model is developed using the concepts derived from input-output (I-O) analysis, a method used to determine linear relationships between components of a complex system (Leontief, 1936). The I-O method is traditionally used in analyzing the interdependency of global economic sectors but is now widely used in similarly structured systems such as industrial complexes (Yazan et al., 2016; Kuznetsova et al., 2017) and bioenergy parks (Benjamin et al., 2015b).

A recent work of Benjamin et al. (2017) used a P-graph approach to criticality analysis in bioenergy parks and demonstrated that it can be an alternative to the I-O based algebraic method (Benjamin et al., 2015a). P-graph is a graph theory and combinatorial algorithm-based methodology that is developed by Friedler et al. (1992a) to solve process network synthesis (PNS) problems. The advantages of this approach are the P-graph software's ability to model various I-O systems and correspondingly display the results through a graphical interface. Aside from these, the method can provide optimal and near-optimal solutions, the latter factor being important in many practical decision making situations (Friedler, 2015).

P-graph based approaches are used in designing biomass-based systems in order to attain sustainability as demonstrated by Lam et al. (2012). The P-graph method is also used to solve similarly structured problems in polygeneration systems (Tan et al., 2014), urban infrastructures (Tan et al., 2015), economic sectors (Aviso et al., 2015), biorefineries (Atkins et al., 2016), biomass corridors (How et al., 2016), industrial complexes (Tan et al., 2016), waste-to-energy networks (Walmsley et al., 2017), workforce organizations (Aviso et al., 2017), and resource conservation networks (Lim et al., 2017a, 2017b). Recent developments, as well as future directions, in the application of P-graph are also discussed in the review papers of Klemeš and Varbanov (2015) and Varbanov et al. (2017).

Another application of the P-graph methodology that is yet to be explored is in the area of risk analysis. As defined by Kaplan and Garrick (1981), risk analysis is a qualitative and quantitative tool to answer these triplet questions: What can go wrong? What is the probability of its occurrence? What are the consequence of that event? The answer to the last question can be answered by rigorous modeling techniques in which the P-graph approach can solve. Capacity disruptions or inoperability greatly affects the performance of integrated systems when not considered prior the design stage. Tan et al. (2014) utilized the P-graph approach to optimally allocate products streams in a polygeneration system in case of capacity disruption scenario and the same approach is applied to industrial complexes levels (e.g., aluminum complex) in the subsequent study by Tan et al. (2016). On the recent work of Benjamin et al. (2017), the P-graph approach is extended as an alternative method to criticality analysis via an algebraic I-O based method to bioenergy parks. These proposed methods however, were not able to incorporate multiple disruption scenarios both in the supply and demand side. Such uncertainties when not properly addressed are crucial in the long-term sustainability of bioenergy parks or other integrated biomass-based systems (Seay and Badurdeen, 2014; Bairamzadeh et al., 2018). To date, P-graph is not yet applied to criticality analysis with multiple supply-side and demand-side disruptions in bioenergy parks or IBS in general.

In this work, a P-graph approach is developed for criticality analysis of bioenergy parks while considering multiple supply-side disruptions and uncertainties in product demands. This work results in robust bioenergy parks that anticipates multiple capacity disruptions as well as potential variations in the demand for bioenergy products. In addition, this method is important in determining appropriate risk mitigation strategies for potential supply and demand perturbation scenarios. Zio (2016) argued the need for conducting more research on risk analysis of complex systems in his recent paper and this work can provide valuable insights in the area of vulnerability and critical infrastructure protection in bioenergy parks. The rest of the paper is as follows: a problem statement and the general framework are discussed next. The P-graph based methodology is then presented and the corresponding bioenergy park case study to demonstrate the proposed approach. A section discussing the supply-side and demand-side disruption is then presented respectively. Finally, conclusions and future research works related to this study are discussed towards the end of the paper.

2. Problem statement

The general framework for the multi-disruption criticality analysis using the P-graph method is stated as follows. A bioenergy park with n number of bioenergy plants is assumed. Each component plant produces a specific product stream and is characterized by fixed ratios of input and output streams using material or energy balance. The network topology or input-output links is known a priori. Using a baseline net output of product streams, the capacity of each bioenergy plant is determined via the P-graph software. *For the supply-side disruptions*: given a scenario, p number of component plants (i.e., $p \geq 2$) are disrupted. This multiple disruption

approach is similar to the method developed by Benjamin et al. (2015b) via input-output modeling. Criticality analysis is performed to determine the reduction in the net output of product streams affected by the disruption. The average net output reduction in the entire bioenergy park is then calculated per scenario. *For the demand-side disruptions*: *q* number of demand perturbation scenarios are assumed. For each scenario, the demand for one product stream is increased to determine its effect in the performance of the bioenergy park during capacity disruptions. Criticality analysis is again conducted to determine the change in the net output of each product stream in various demand perturbation scenarios. The detailed discussion on the methodology for criticality analysis using I-O method is found in Benjamin et al. (2015a) and via P-graph approach in Benjamin et al. (2017). Fig. 1 shows the general framework for the multi-disruption criticality analysis in bioenergy parks using P-graph methodology.

3. P-graph methodology

The P-graph methodology is a graph theoretic framework developed to solve PNS (Friedler et al., 1992b). The approach is based on five axioms (Friedler et al., 1992a) and utilizes efficient algorithms for determining maximal structures (Friedler et al., 1993). These axioms describe in detail the information that is present in PNS problems. One of the advantages of this method is its capability to determine both optimal and near-optimal solutions of a given problem (Tan et al., 2017a) when compared to other mathematical programming methods (e.g., mixed integer linear programming models). Also, the P-graph's software interface enables the user to determine the results visually is another advantage, this is validated by the study of Lam et al. (2016) via a survey of undergraduate students' experience in using the software.

The P-graph uses two kinds of vertices to form the bipartite graph. The M-type vertex (i.e., dots) represents material or energy flows and the O-type vertex (i.e., horizontal bars) represents the operating units in a given network. In this work, the M-type vertices are the bioenergy products (as well as raw materials) and the O-type vertices are the bioenergy plants. These vertices are then connected by arcs in order for the P-graph framework determine the solution to the PNS problem. However, recent studies demonstrate that these vertices may represent other materials or activity such as monetary units in an economic sector (Aviso et al., 2015) or as available workforce in organizations (Aviso et al., 2017). Thus, the P-graph framework can be further extended to solve analogous structures beyond the traditional PNS problems.

On the other hand, the three algorithms embedded in the P-graph method are as follows. First, the maximal structure generation (MSG) is a rigorous superstructure generated from all possible solution structures (i.e., the number of ways producing the desired final product). Second, using this information, the solution structure generator (SSG) determines then the subset of all combinatorially feasible structures. Lastly, the accelerated branch-and-bound (ABB) algorithm efficiently determines the optimal as well as non-optimal solutions of the PNS. These main algorithms also utilize the information set by the five axioms and the given constraints of a particular problem. These axioms (Friedler et al., 1992a) are stated as follows: First, every final product is represented in the graph. A vertex of the M-type has no input if and only if it represents a raw material. Every vertex of the O-type represents an operating unit defined in the synthesis problem. Every vertex of the O-type has at least one path leading to a vertex of the M-type representing a final product. Lastly, if a vertex of the M-type belongs to the graph, it must be an input to or output from at least one vertex of the O-type in the graph. The P-graph software (P-graph, 2017) is used in developing the structure of the PNS. This includes drawing the respective operating units, corresponding product streams, and the connecting arcs. The software also enables the user to encode exogenously defined parameters or problem constraints such as measurement units, unit capacities, material flows, and costs.

In this work, the multiple capacity disruptions and the net output of unaffected product streams are encoded as constraints in the P-graph software. The resulting reduction in the net output per scenario is solved after running the model. This approach will be repeated in all supply-side disruption and demand-side perturbation scenarios. The results displayed by the software will then be subjected to analysis as shown in the general framework.

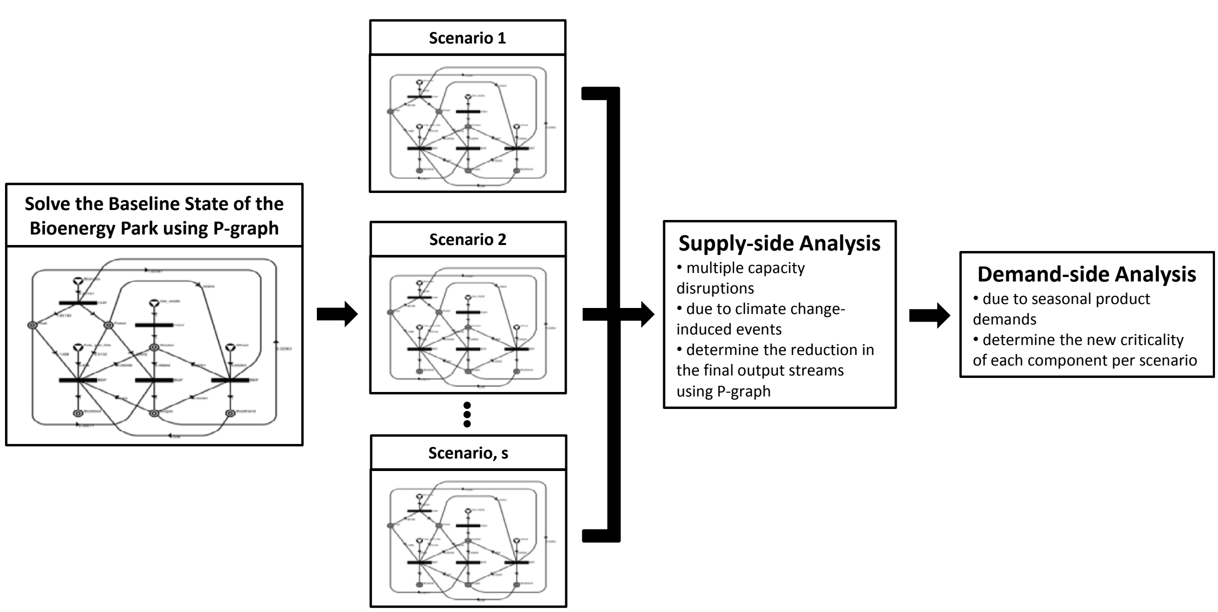

Fig. 1. General framework for the multi-disruption criticality analysis using P-graph methodology.

4. Case study: bioenergy park

The hypothetical bioenergy park case study shown in Fig. 2 is adapted from the work of Benjamin et al. (2015b). This bioenergy-based EIP consists of the following bioenergy plants and their corresponding product streams. Bioethanol is produced from a wheat-based bioethanol plant (BEP) and vegetable oils are used to produce biodiesel in the biodiesel plant (BDP). The biogas plant (BGP) utilizes waste from other bioenergy plants and external sources in order to generate biogas. Lastly, biomass feedstocks are used to produce heat and power in a combined heat and power (CHP) plant. The CHP plant also provides the required process utilities (i.e., heat and power) by other component plants in the bioenergy park as seen from the linkages. CHP plants are usually functioning as “anchor tenants” in an EIP primarily due to its ability to supply common utilities to other plants and thus help in the sustainability of the EIP (Wang et al., 2006).

Table 1 shows the material and energy balance ratio for each bioenergy plant normalized based on the primary product stream. For example in the BEP column, in order to produce 1 L/h of bioethanol output, 0.259 kW of power and 0.00381 m^3/h of biogas are required as inputs. The net output of the product streams are also shown in the last column and this will be used as the baseline demand for calculating the required plant capacities. The complete baseline state (i.e., flows of raw materials, products, and capacity of component plants) of the bioenergy park is shown in Fig. 2. The baseline capacity of the bioenergy plants were determined using the P-graph software (Benjamin et al., 2017) and the model displayed the results with negligible computing time. It can be seen from the figure that the required capacity for each bioenergy plant exceeds the net output due to internal requirements within the network. The P-graph version of the input-output flow diagram of the bioenergy park is shown in Fig. 3. The next section describes the criticality analysis of the bioenergy park under multiple supply-side disruptions.

4.1. Supply-side disruption

Supply-side disruptions in bioenergy parks can be caused by climate change-induced events that may potentially decrease the available biomass feedstocks for bioenergy production (Langholtz et al., 2014). Consequently, this disruption is proportional to the ability of a particular bioenergy to produce the baseline production level, this thus results in capacity inoperability. In this work, multiple supply-side disruption scenarios are assumed. In each scenario, more than one bioenergy plant is disrupted and therefore the

Table 1
Process data for the baseline state of the bioenergy park (Adapted from Benjamin et al., 2015a).

Product stream	CHP	BEP	BDP	BGP	Final output
Power, kW	1	−0.259	−0.0132	−0.4354	22,000
Bioethanol, L/h	0	1	−0.236	0	25,000
Biodiesel, L/h	0	0	1	0	20,000
Biogas, m^3/h	−0.02963	−0.00381	−0.004	1	1,000

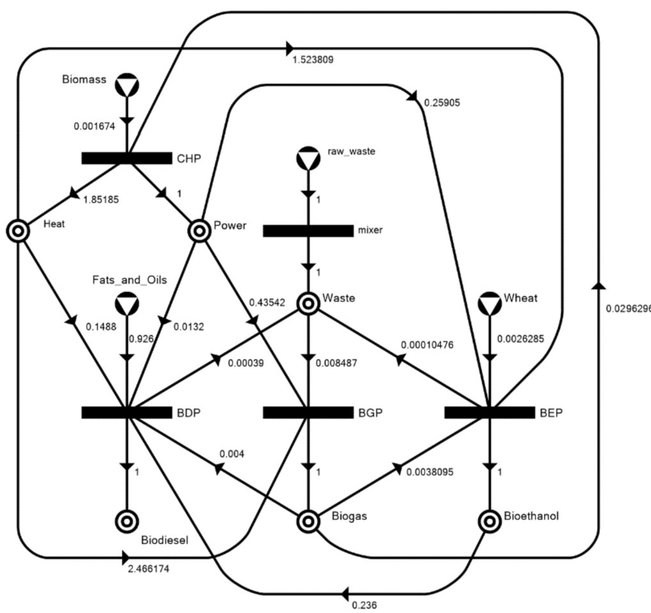

Fig. 3. Input-output flow diagram of the bioenergy park using P-graph.

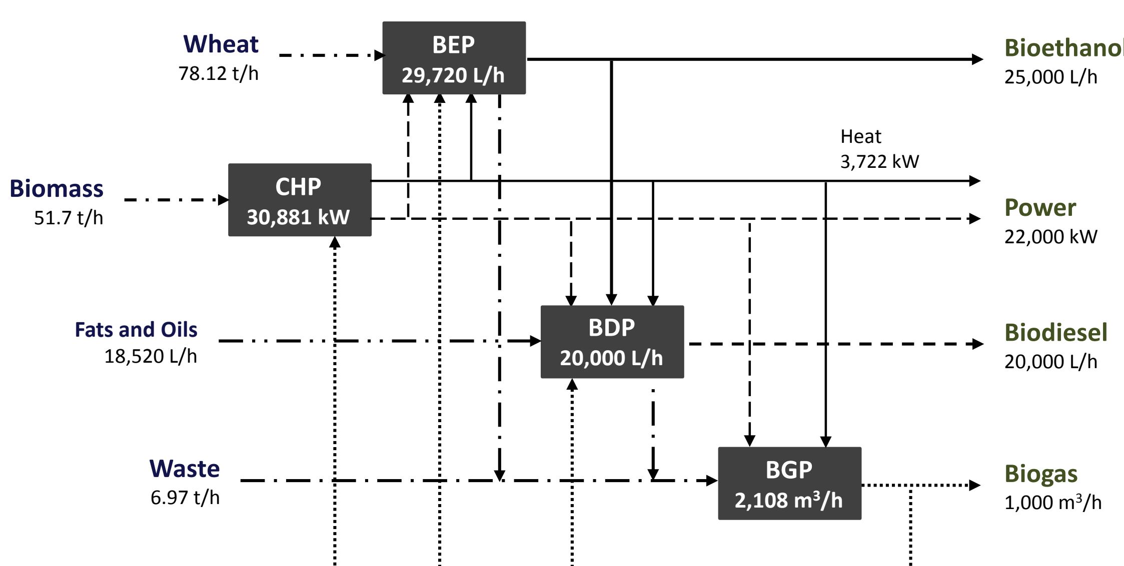

Fig. 2. Process flow diagram of the bioenergy park (Adapted from Benjamin et al., 2015a).

corresponding product streams as well. The demand for unaffected product streams are assumed to be at the baseline levels, this approach ensures the direct measurement of the disruption consequences (i.e., average reduction in net output). The total number of possible disruption scenarios are determined via simple enumeration due to the small number of bioenergy plants present in the network. Table 2 shows all the supply-side disruption scenarios used in this study. Scenarios 1 to 6 are 2-plant disruptions and Scenarios 7 to 10 are 3-plant disruptions. Using the baseline state of the bioenergy park, a 5% reduction in capacity per plant is assumed. This means that for Scenario 1, the capacity of BGP is decreased to 2,003 m^3/h from 2,108 m^3/h and the production level of BDP is 19,000 L/h instead of 20,000. It is also assumed that the final output for power (i.e., 22,000 kW) and for bioethanol (i.e., 25,000 L/h) are fixed. These values are encoded in the P-graph software as exogenous constraints. The proposed P-graph approach will be used to solve the reduction in the affected product streams and the results will be compared to the study of Benjamin et al. (2015b) that used an algebraic I-O based model for criticality analysis.

Criticality analysis via the P-graph method is then applied to determine the reduction in the biogas and biodiesel products respectively. Due to space limitations, the P-graph representation of the disruptions were just limited to Scenarios 1 and 7. These two scenarios represent the disruption of 2 bioenergy plants and 3 bioenergy plants, respectively. The corresponding P-graph representation of the supply-side disruptions are then shown in Figs. 4 and 5. The complete results of the calculations are also presented in Table 2 and shows the reduced final output of the affected product stream. It can be seen from the table that for Scenario 1 the net output for biogas is decreased to 903 m^3/h or a fractional change of 0.097 using the baseline value of 1,000 m^3/h; and a final output of 19,000 L/h for biodiesel or a reduction of 0.05.

Fig. 6 shows the average net output reduction (i.e., fractional change) in the bioenergy park per scenario. S1 to S6 (red colored bars) are 2-plant disruptions, while S7–S10 (purple colored bars) are 3-plant disruption scenarios. It can be seen from the figure that the resulting reduction per scenario is influenced by the number of disrupted bioenergy plants. This suggests that greater risk mitigation strategies should be in placed when anticipating multiple plant or component failure due to the magnitude of the consequence. On the other hand, the variations in the trend among similar number of disrupted plants is based on the connectivity of each plant within the network. As observed by Benjamin et al. (2017), the disruption of critical components (i.e., highly connected bioenergy plants) results in greater net output loss due to the necessity to supply the internal requirements within the bioenergy park.

The P-graph method developed will enable risk managers draw risk-based insights to prepare risk mitigation strategies such as considering different inventory strategies (Barker and Santos, 2010), allowing multiple sources or linkages (Zhu and Ruth, 2013), and providing redundant or backup facilities (Andiappan

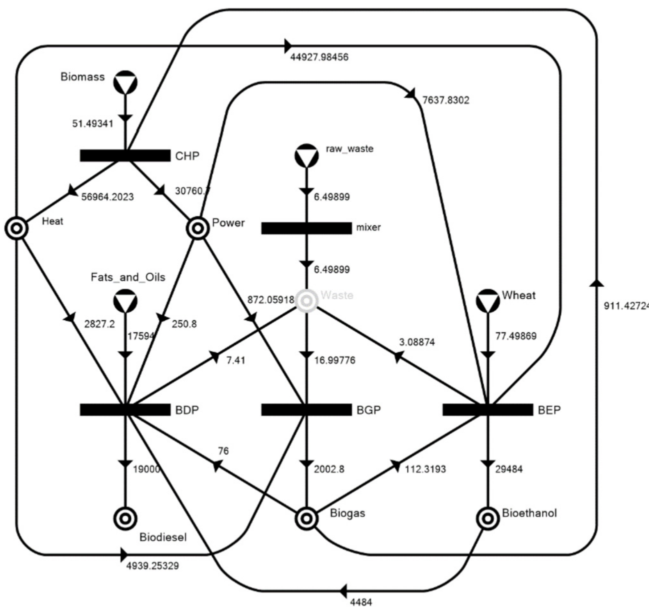

Fig. 4. Disrupted state of the bioenergy park in Scenario 1 (supply-side disruption).

Table 2
Reduced final output of affected streams in the supply-side disruption scenarios.

Scenario	Disrupted plants	Affected product stream	Reduced final output
Scenario 1 (S1)	Biogas plant, m^3/h	Biogas, m^3/h	903
	Biodiesel plant, L/h	Biodiesel, L/h	19,000
Scenario 2 (S2)	Biogas plant, m^3/h	Biogas, m^3/h	940
	CHP plant, kW	Power, kW	20,504
Scenario 3 (S3)	Bioethanol plant, L/h	Bioethanol, L/h	23,750
	Biodiesel plant, L/h	Biodiesel, L/h	19,000
Scenario 4 (S4)	Bioethanol plant, L/h	Bioethanol, L/h	23,525
	CHP plant, kW	Power, kW	20,856
Scenario 5 (S5)	Biogas plant, m^3/h	Biogas, m^3/h	913
	Bioethanol plant, L/h	Bioethanol, L/h	23,525
Scenario 6 (S6)	CHP plant, kW	Power, kW	20,548
	Biodiesel plant, L/h	Biodiesel, L/h	19,000
Scenario 7 (S7)	Biogas plant, m^3/h	Biogas, m^3/h	917
	Biodiesel plant, L/h	Biodiesel, L/h	19,000
	Bioethanol plant, L/h	Bioethanol, L/h	23,750
Scenario 8 (S8)	Biogas plant, m^3/h	Biogas, m^3/h	945
	Biodiesel plant, L/h	Biodiesel, L/h	19,000
	CHP plant, kW	Power, kW	20,570
Scenario 9 (S9)	Biogas plant, m^3/h	Biogas, m^3/h	946
	CHP plant, kW	Power, kW	20,878
	Bioethanol plant, L/h	Bioethanol, L/h	23,525
Scenario 10 (S10)	CHP plant, kW	Power, kW	20,878
	Biodiesel plant, L/h	Biodiesel, L/h	19,000
	Bioethanol plant, L/h	Bioethanol, L/h	23,750

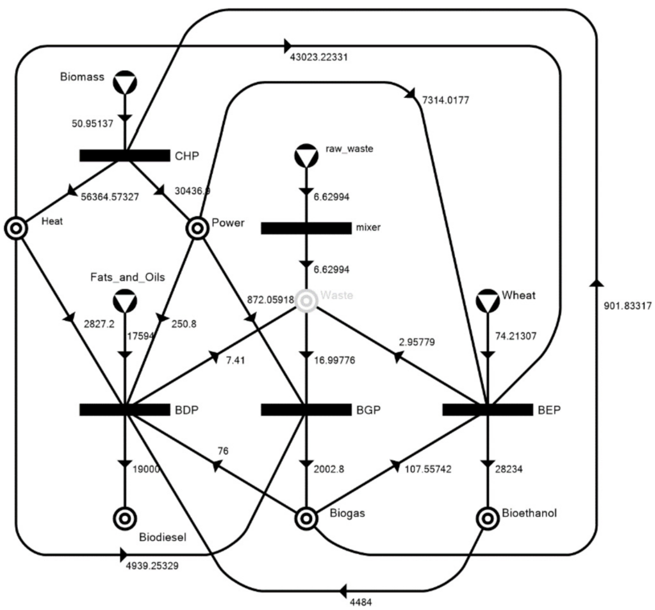

Fig. 5. Disrupted state of the bioenergy park in Scenario 7 (supply-side disruption).

and Ng, 2016). These strategies will help in the development of more sustainable and robust bioenergy parks under normal or multiple disrupted conditions. In this supply-side disruption criticality analysis, the equivalent results to the earlier work of Benjamin et al. (2015b) was obtained using the proposed P-graph approach. This method will be further extended in the next section to incorporate uncertainties in the bioenergy products through various demand perturbations.

4.2. Demand-side disruption

A robust and sustainable bioenergy park must be able to anticipate fluctuating and unpredictable market demands for bioenergy products (Hong et al., 2016). This is due to the fact that product demands will affect the investment, planning, and eventually the revenue of a particular bioenergy system (Tay et al., 2013). This study further extends the P-graph approach to consider seasonal variations by having multiple product demand perturbations scenarios.

Similar to the supply-side disruption approach, a 5% reduction in the production level of each bioenergy plant is assumed. This represents a proportional supply-side decrease in the availability of biomass feedstocks and other raw materials. The method also assume that this will result in a decreased net output in the corresponding product stream. In addition, the internal demands within the bioenergy park must be satisfied first, thus, the net output reduction is not necessary equal to the degree of capacity disruption. The value of the reduced capacity and the baseline demand for unaffected product streams are encoded in the P-graph software as constraints.

For the demand-side uncertainty analysis, the effect of varying the product demand to the criticality each product stream was determined. For each scenario, the net output of one particular stream is increased by 5% and the rest are fixed at the baseline value. Four scenarios were considered in this section that represent the perturbation in each of the product demands. For example, in Scenario I, the demand for power is increased to 23,100 kW from 22,000 kW. Criticality analysis was again conducted for each bioenergy plant per scenario and the results are presented in Table 3. The corresponding P-graph representation of the demand-side disruption for Scenario I only are then shown in Figs. 7–10. It can be seen from Table 3 that net output reduction in the multiple demand scenarios are greater compared to the value of the baseline scenario. This is due to the additional demand that must be supplied first to other interdependent bioenergy plants within the network. On the other hand, a decrease of 5% in the demand for biogas (i.e., from the baseline) resulted in 5.68% change in the net output compared to the value of 14.67% (i.e., Scenario IV). To add, a simultaneous increase in the demand for both power and biogas resulted in 11.45% and 17.81% reduction in net output, respectively. The changes in the demand therefore causes further amplification

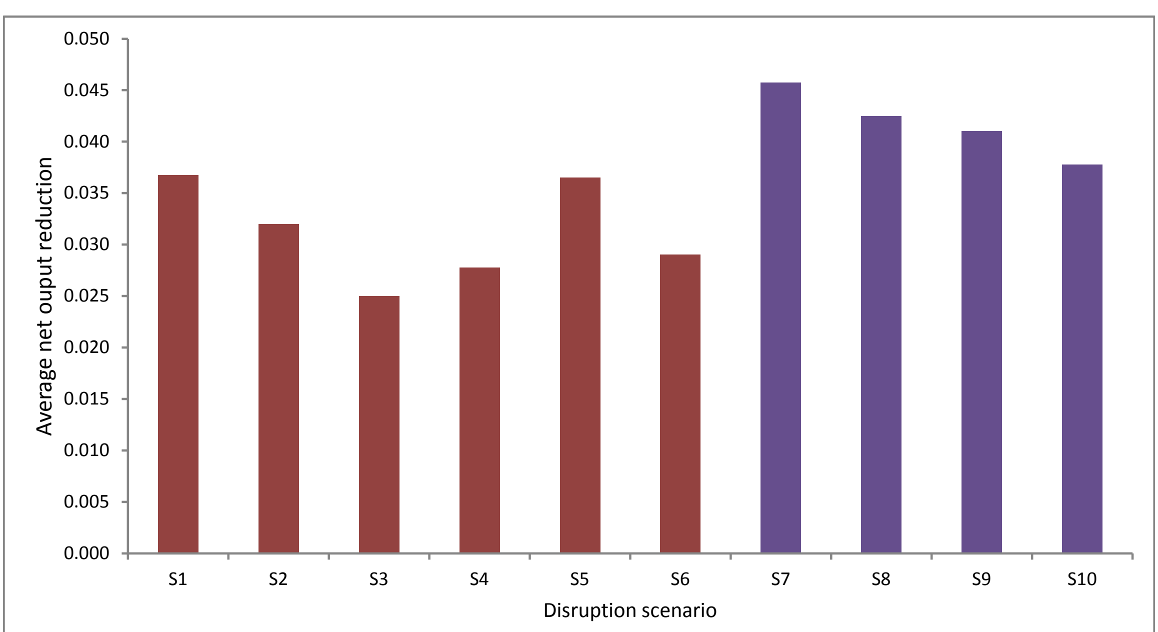

Fig. 6. Average net output reduction in the bioenergy park in the supply-side disruptions.

Table 3
Reduced final output of product streams in the demand-side disruption scenarios.

Disrupted bioenergy plant	Affected product stream	Baseline final output	Adjusted final output	Baseline scenario	Reduced final output			
					Scenario I (SI)	Scenario II (SII)	Scenario III (SIII)	Scenario IV (SIV)
CHP	Power, kW	22,000	23,100	20,476	20,476	20,150	20,340	20,454
BEP	Bioethanol, L/h	25,000	26,250	23,514	23,514	23,514	23,278	23,514
BDP	Biodiesel, L/h	20,000	21,000	19,000	19,000	19,000	19,000	19,000
BGP	Biogas, m^3/h	1,000	1,050	896	864	882	889	896

or attenuation of the disruption within the bioenergy park and thus, must be considered in preparing specific risk mitigation strategies.

The percentage change in the final output of the bioenergy plants in the demand perturbation scenarios are presented in Fig. 11. The figure shows the sensitivity of the net output (i.e., criticality) to the variations in the demand of a particular product stream. It can be seen in all scenarios that the criticality of the perturb product stream is increased compared to the baseline demand due to additional requirements outside the network. Such seasonal occurrence should be anticipated in the planning stage of the bioenergy park to attain a more sustainable system. The system should be designed to allow operational flexibility in production capacity, thus reducing the chance of having an under-capacity bioenergy park. Using the baseline demand, the criticality rankings are shown in Table 4 as adapted from Benjamin et al. (2015a) and using the results from this work. This provides an insight to risk managers on which is the most critical component in the network that needs the greatest attention for risk mitigation. However, it can also be seen in the same table that the risk rankings are also influenced by variations in the demand. This observation is significant since it will have an impact in the appropriate risk mitigation steps to be implemented. For example, in Scenario II, the

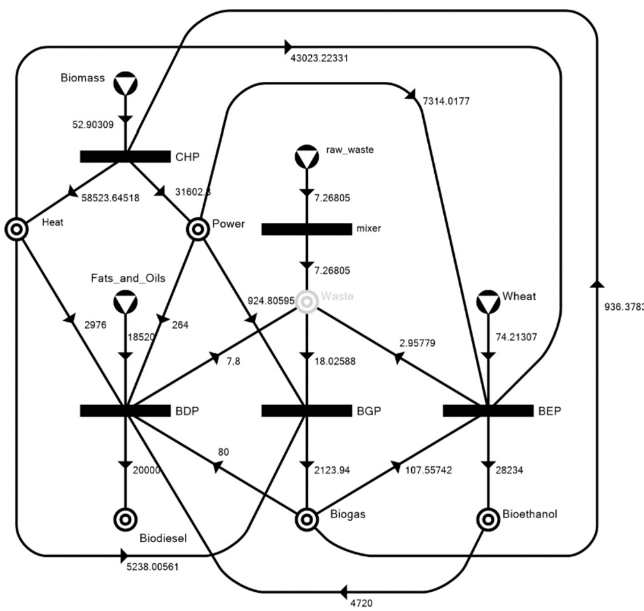

Fig. 8. Disrupted state of the bioenergy park in Scenario I for bioethanol (demand-side disruption).

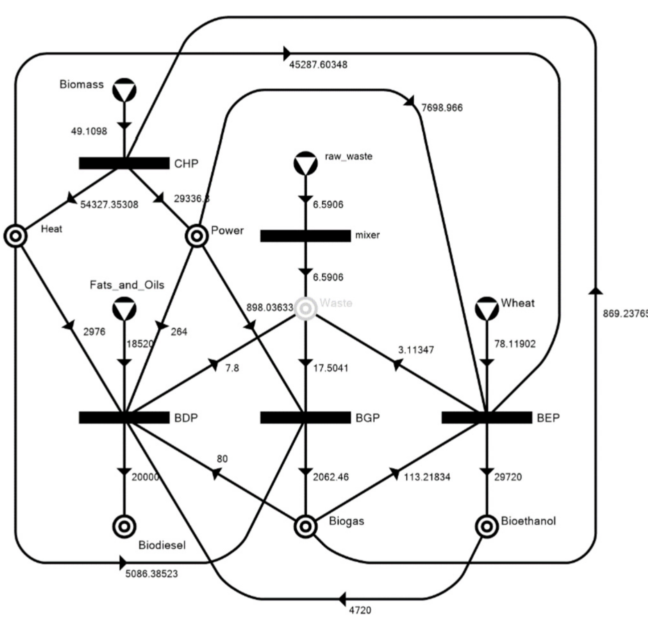

Fig. 7. Disrupted state of the bioenergy park in Scenario I for power (demand-side disruption).

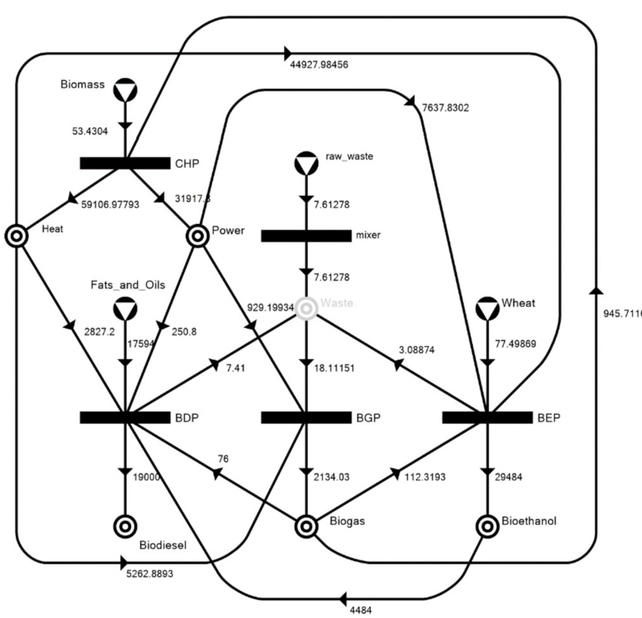

Fig. 9. Disrupted state of the bioenergy park in Scenario I for biodiesel (demand-side disruption).

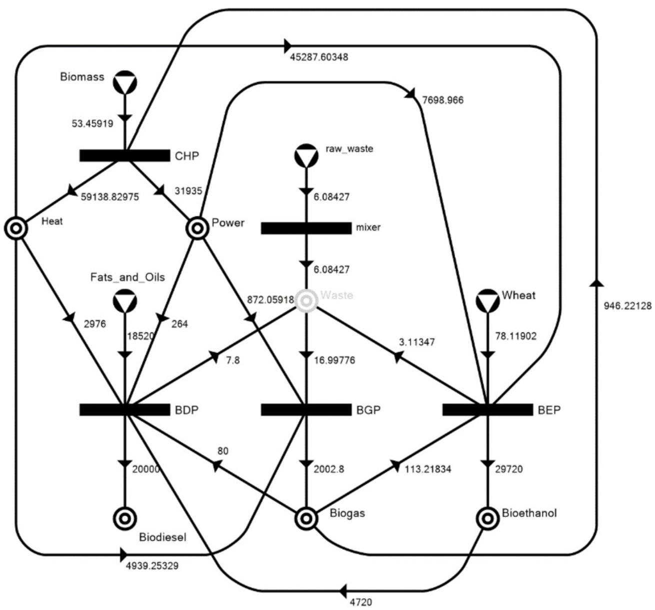

Fig. 10. Disrupted state of the bioenergy park in Scenario I for biogas (demand-side disruption).

second most critical bioenergy plant is the BEP not the CHP; as compared to the baseline scenario and Scenario I. This shows that each demand perturbation scenario requires a different strategy to address criticality or risk. Aside from the risk mitigation strategies suggested in the previous section, seasonal variations in the demand can be addressed by using robust optimization approaches that considers multiple probabilistic scenarios in the design stage of the biorefinery (Tay et al., 2013), through integrating several risk analysis tools that considers systems-perspective approaches (Seay and Badurdeen, 2014), and via debottlenecking methods to increase flexibility of capacities of existing facilities (Hong et al., 2016). The deterministic nature, negligible computing time, and

Table 4
Risk ranking of bioenergy plants based on fractional net output reduction.

Disrupted bioenergy plant	Baseline	Scenario I	Scenario II	Scenario III	Scenario IV
BGP	1	1	1	1	1
CHP	2	2	3	3	2
BEP	3	3	2	4	3
BDP	4	4	4	2	4

ease of use of the P-graph interface are the advantages of the method developed in this work and this can be of practical use in actual industrial setting.

5. Conclusions

A P-graph approach to criticality analysis in bioenergy parks with multiple supply-side and demand-side disruptions was developed in this work. This is a novel extension of the P-graph method developed by Benjamin et al. (2017) that determines the reduction in the net output of product streams brought about by simultaneous climate change-induced events and seasonal variations in the demand. The insights from this work can be used to develop flexible bioenergy parks that will tolerate anticipated supply and demand-side perturbations. It can be seen from the results that the disruption consequence for multiple-plant inoperability is highly influenced by the number of disrupted plants. Equivalent results were also obtained in the criticality analysis of multiple supply-side disruptions via the P-graph approach when compared to the previously developed algebraic I-O based method (Benjamin et al., 2015b). In addition, criticality rankings of the bioenergy plants greatly vary in the different demands-side uncertainty scenarios, thus, this will require risk-specific mitigation strategies. Future works will focus on using a Monte Carlo simulation-based method in assessing the sensitivity of the bioenergy park from probabilistic uncertainties (Tan et al., 2007) and in developing multi-period models (Aviso et al., 2016).

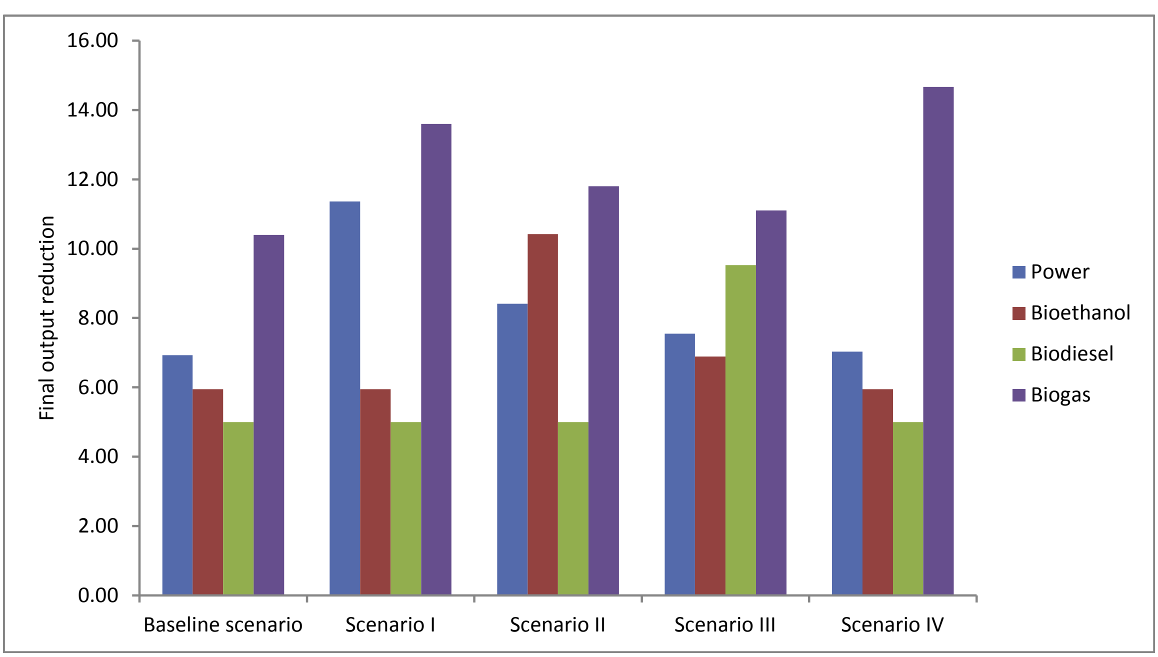

Fig. 11. Percentage net output reduction in the bioenergy park in the demand-side disruptions.

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List of symbols

ABB	Advanced branch-and-bound
BDP	Biodiesel plant
BEP	Bioethanol plant
BES	Biomass energy systems
BGP	Biogas plant
CHP	Combined heat and power plant
EIP	Eco-industrial parks
GHG	Greenhouse gas
I-O	Input-output
IS	Industrial symbiosis
IBS	Integrated bioenergy systems
IES	Integrated energy systems
MSG	Maximal structure generation
PNS	Process network synthesis
SSG	Solution structure generation

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